Stress Detection:

Detecting, Monitoring, and Reducing Stress in Cyber-Security Operation Centers

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Problem Statement

The accessibility of technology and the IOT (Internet of Things) available at our fingertips, twenty-four hours per day, can quickly become a technological overload. For many reasons, this can be problematic for people working in front of computers, whether at home or in an office setting. Our "first responders" in cybersecurity, the analyst that works consistently in front of multiple computer screens and mobile devices to protect data from various forms of attacks are at a higher risk. Unmanaged stress can lead to poor job performance such as multiple health-related absences, missed warning signals on possible cyberattacks, and an overall lack of enthusiasm for the work needed to be done.

Conversations on the topics of cybersecurity, stress, and anxiety are not usually discussed in the same setting. My objective is to show a correlation between these topics and to detect, reduce, and finally offer reasonable resolutions moving forward. This generates many questions with the first question being how to detect and monitor stress. Furthermore, how do we capture this data for analysis? Additional questions are how do we create an early recognition and detection system to alert the Cybersecurity Analyst before his or her job performance is severely affected?

I propose to use multi-model sensors along with Facial Expression Recognition software to detect stress as it is being triggered to gain a better understanding and to answer as many of these questions as possible. The intended sensors to use will be smartwatches, GSR sensors, and chairs equipped with various biosensors. Additionally, for in-house testing and experimentation, computers with webcams, video recording, and emotion recognition software are installed to capture data for data analysis.

ABSTRACT

This literature review is an attempt to combine and define three different broad topics by answering several questions by reviewing as much literature as possible on studies and experimentation that have already been done. The first question being asked and discussed is, how to reduce or offer a resolution to stress during working hours for cybersecurity specialists? Firstly, to gain an understanding of how to move forward with answering this question of how to reduce stress, reviewing a few background and current topics will set the tone for further discussion.

Starting with the current topic of the advancement of technology. Obviously, technology is at our fingertips and accessible, twenty-four hours per day with all types of devices such as laptops, watches, and cell phones. There are also many other ways to access the Internet outside of the home or office such as smart TVs, smart cars, and public Wi-fi hotspots, all of which enable us to have access to the IOT (Internet of Things) almost everywhere and at any time. As technology advanced over the years, curiosity has also grown on how to monitor human emotions and how these emotions correlate with technology. In addition to the advancement of technology and the IOT, there is also growth in Big Data. The growth in Big Data stemmed from social media, sentiment analysis, text mining, and Ecommerce. (Liao, Chen, & Tai, Apr 2018)

There are many questions about how human emotions affect technology, or better yet, how does technology affect human emotions? How do human emotions and mental health issues such as stress and anxiety affect people who choose to work in stressful environments? To be even more specific, how do high-stress levels affect the performance of Cybersecurity Analysts? How do we create an early recognition and detection system to alert the Cybersecurity Analyst before his or her job performance is severely affected?

INTRODUCTION

It is widely known that high levels of stress and anxiety that are left unmanaged can be dangerous. Untreated stress or poorly managed stress levels can lead to many health complications. Not only do health complications in individuals, but these complications can negatively affect job performance which can lead to a domino effect of problems affecting many others. The body and mind can be seriously affected by mental stress rendering someone unable to concentrate, with difficulty in thinking with a clear mind, poor job performance, and neglect of personal responsibilities and health. All these symptoms can lead to a mental breakdown. (Chickerur & Hunashimore,) Unfortunately, many people do not take the time to properly take care of their mental health. Due to fast-paced lifestyles and the unavoidable use of technology, human stress levels are unmanaged and extremely high. The difficult task of creating a work-life balance between home life, personal self-care, and work equals pressure to keep it all under control. (Parab, et al., 2020)

At this point, there is a need to switch directions to define the different definitions for Cybersecurity. Cybersecurity is known for the protection of all computers and electronic devices that are connected to a network from malicious cyberattacks. (Craigen, et al., 2014) Stress and anxiety are two different terms with different definitions. These terms are used interchangeably as aforementioned. In discussing the long-term effects of both stress and anxiety, their symptoms are similar. Understanding the difference between the two, the definitions of both stress and anxiety will be discussed in depth. Stress is the feeling of emotional or physical tension. It comes from any event that makes someone feel frustrated, angry, or nervous. Stress is the body's reaction to a challenge or demand. Whereas the definition of Anxiety is the feeling of fear, dread, and uneasiness.

Anxiety causes someone to sweat, feel restless and tense, and have a rapid heartbeat. For example, the feeling of anxiousness when faced with a difficult problem at work, before taking a test, or before making an oral presentation. (Giannakakis et al., 2017) In addition to combining three distinctly different terms, the goal of this study is to also determine at what point someone feels stress or anxiety. The method of how to detect these emotions is by using facial cues from video monitoring with facial expression recognition software and capturing the data using biosensors.

REVIEW OF LITERATURE

This literature review will examine and analyze other studies, journals, articles, and tests, to gain an overview of earlier attempts to detect stress. The aim of this proposal is to detect and study stress and anxiety in participants by videoing teach of them in experimental environments and studying their facial cues using various stimuli and applying these findings to statistical and data analytic formulas. The formulas will be studied, and data will be extracted from the different facial cues at various states, such as neutral, relaxed, stressed, and anxiousness. While studying the face, obviously, the entire face consists of the forehead, eyes, eyebrows, nose, lips, and skin color. (Giannakakis et al., 2017). When you think about what goes on with someone's face when stress is triggered, each facial feature just mentioned is affected and has a range of motion. The skin normally changes to a pale color or more reddish hue, based on emotion. The two key modes of response to these triggers are "fight or flight," which are two primal feelings for safety and survival in the human body. Anxiety is usually a feeling that is not related to outside triggers or external cues.

Whereas stress is your body's direct response to daily demands and various triggers. Nevertheless, stress and anxiety can have physical, mental, and cognitive effects on the body.

(Giannakakis et al., 2017) This review further explains that the studies done on humans and animal experiments have shown that these effects in the long term, can lower the immune systems and have higher risks of certain types of cancer.

Stress and anxiety are also linked to other common symptoms such as headaches, hypertension, lower back, and neck pain. (Giannakakis et al., 2017) Stress can be detected through bio-signals as well. Bio-signals are time-varying measures of the human body's process that can be divided into two main categories. (Giannakakis et al., 2017) When associating the reviewed literature with this study, it is projected that prolonged stress in a particularly stressful working environment will have negative effects on the sensitive nature of the job of cybersecurity.

The two main categories are Physical signals and Physiological signals. Physical bio-signals are measures of how the body moves as the result of muscle activity which also includes pupil size, eye blinks, head, body, arms, and leg position or movements. Respiration, facial expressions, and voice are a part of the physical bio-signals as well. Physiological signals are more related to the body's vital functions, such as cardiac activity which are normally detected with sensors attached to the body such as the Electrocardiogram [ECG] and the Blood Volume Pulse [BVP]. (Giannakakis et al., 2017) Disruption of the normal breathing patterns, brain function and other upper respiratory functions which are correlated with emotional stress and anxiety signals can be detected using an EEG sensor. One of the effects of stress is sweating in the palm of the hands, on the forehead, and armpits. The Galvanic Skin Response (GSR) sensor can be used to detect stress with the activation of these sweat glands. (Giannakakis et al., 2017) This review also explains in further detail how stress and anxiety affect the human face. There are various categories of facial features connected with stress and anxiety.

The categories are the Head (head movements, skin color), the Eyes (blink rate, eyelid response, eyebrow movements), the Mouth (mouth shape, and lips whether frowning or smiling), the Gaze (gaze direction, saccadic eye movement), the Pupil (pupil size as it dilates). The task of determining how much stress and anxiety affect workday performance and employee alertness begins with first delving deeper into what triggers stress and anxiety attacks in different people in a work environment. In stressful work environments such as call centers, specifically Cybersecurity Operations Centers, it is shown that the highly sensitive information being attacked can cause high levels of stressful triggers for an individual. (Giannakakis et al., 2017)

These types of workplace environments are especially stressful because of the nature of the day-to-day job responsibilities. Cybersecurity alone is an elevated risk, then by adding the element of protecting high-profile critical information as well as large sums of money, the stakes become even higher. The task of a professional cybersecurity agent or analyst is to protect and secure the computer network of a business or government entity from malicious digital attacks. The day-to-day operations are to manage, watch, analyze, and secure the company's information minute by minute. As imagined, this can result in mental burnout and fatigue quickly. It is common that the operators will experience disabling, chronic stress, and anxiety symptoms which can develop into other mental and physical health issues if left untreated. (Dykstra & Paul)

Studies have shown that mental stress and anxiety are very dangerous conditions and as stated previously many people go about their daily lives with seriously elevated stress levels. Doctors have stated that most professionals, students, and full-time employees with families seem to show the highest stress and anxiety levels. (Parab, et al, 2020) To completely understand how to detect anxiety and stress in employees that work in highly stressful environments, a foundation of understanding human emotions must be established.

After establishing a basic understanding of the various emotions, then learning how the human face displays each emotion is next. The following step would be deciding how each of these emotions will be captured and after that, the process of analysis is determined. There are many articles and journals discussing experiment after experiment on stress detection and emotion recognition. Furthermore, the process of facial expression or emotion recognition is the process used to determine the emotional or mental state of an individual. (Parab, et al., 2020)

Authors of a recent study successfully used a face detection model to basically use features of the face to detect emotions in individuals. For example, the study underscored what scientists had previously discovered drowsiness with droopy, heavy eyelids that can't seem to stay open is a facial feature and symptom of stress. (Parab, et al., 2020) There are also many studies on using wearable devices that detect various bio-signals that the body gives during different situations. Many of these devices people wear daily to track their steps, blood pressure, and heart rate to aid in weight loss and to track other health issues or concerns.

These wearable devices have proven to be a non-intrusive way to capture important biosignals from the body. (Montesinos, et al., 2019) The wearable devices often are embedded with Pulse Rate Detection systems, or Heart Rate monitors, to track an individual's heartbeat per minute. If not performing some type of cardio exercise to increase the heart rate purposely to aid in weight loss, then the alternative increase in heart rate would only mean stress. (Parab, et al., 2020) In addition to these non-intrusive wearable devices, there is facial expression recognition software to detect, analyze, and display these human emotions. A recent study showed a demonstration of an effective facial expression recognition software and how it can detect human emotions using computer interface technology that will display the various stages of facial expressions.

The different facial expressions range from disgust, neutral, fear, happiness, anger, sadness, and surprise. (Giri, et al., 2022) There are many different wearable devices that can detect multiple bio-signals and offer important contributions to detecting stress levels. Each of these useful devices with these special sensors and their contributions to detecting stress will be discussed in more detail later in this review. Each contribution offers detailed, specific pieces of information on an individual emotional state and mental capacity. (Montesinos, et al., 2019)

Additionally, this article also introduces the foundational experiment in understanding facial expressions along with human behavior with a computer interface. This interface will provide computer code that analyzes each expression. It is safe to say that most humans learn to perceive and identify someone's emotional state through facial expressions early in childhood. Daily decision-making, perceptions, and how we interact with others lie directly in facial expressions.

It is difficult for artificial technology to detect with 100% accuracy because the human face depicts many different expressions that technology simply cannot translate. The simulation described in this journal will detect human expressions and emotions with almost 80% accuracy. (Giri, et al., 2022) Artificial Intelligence and Machine Learning play a key role in training a computer to detect each emotion.

Several studies have shown that wearable and mobile devices successfully detect stress levels by using health parameters based on not only heart rate but also body temperature and the galvanic skin response which is specifically installed to detect the sweat on the skin. (Parab, et al. 2020) There are a few computer models that use code that is in existence today that do a thorough job of detecting emotions by user demand such as emotion detection using Python, OpenCV, and Artificial Intelligence. (Giri et al., 2022)

Furthermore, there are other models that can detect emotions separately with high accuracy. For example, the EEG (electroencephalogram) model which records brain activity can detect positive emotions with 85% accuracy, neutral emotions with 25% accuracy, and up to 10% accuracy of negative emotions. (Giri et al., 2022)

The main purpose or goal of the Emotion Detection Recognition model (EDR) is to detect human emotion with the highest accuracy possible. The experiment used an emotion detection dataset that was found on Kaggle.com which aided in the training model. The dataset found on Kaggle.com is a collection of all human emotions. The training was done by importing the deep-learning Python libraries necessary to carry out the explicit commands and then executing the commands in the Python coding program. Python software can display accurate results by showing the various states of human emotions detected on the face. (Giri et al., 2022)

By implementing the “dlib” library in Python, which is used to detect facial features with up to 68% accuracy. The features concentrate primarily around the perimeter of the face, such as the edges, eyes, nose, and mouth area. (Sengupta, 2021) The results of this experiment using the Python model displayed live facial expressions in front of a webcam. The webcam was set up to record to further study the results. By loading and running the trained model using the dataset from Kaggle.com into Python, each expression made from the face of a human can accurately be displayed. Different phases or steps must occur in a very specific order to achieve the desired results. (Giri et al., 2022)

METHODOLOGY

There are numerous ways to collect bio-signals by using different biosensors. Additionally, there are several types of sensors to collect these signals given by the human body when stress or anxiety is triggered. There are passive sensing technologies and as mentioned previously there are physiological indices. The physiological indices come from measuring the blood pressure, the amylase and cortisol in saliva, and the heart rate. Amylase is the enzyme within the saliva that turns starches in food into sugars. While these measures are dependable, they are impractical because it is almost impossible to collect this type of information consistently. (Koussaifi, et at., 2018)

Then there is the passive sensing technique. This technique consists of using physical activity to collect bio signals. The devices used are implantable electronic cardiovascular devices or polysomnography which detect sleep disorders. There are also pedometers, commercial wristband activity trackers, smartwatches, and smartphones using the appropriate applications installed on the phones to collect this data. (Koussaifi, et al., 2018)

Using wireless body sensors is a relatively new study. Using a Wireless Body Sensor Network is a study of a self-configuring network that consists of small biosensors communicating over radio signals. Many approaches that already exist to detect human stress levels using physiological signals are invasive and time-consuming. Another study that seemed hopeful incorporates radio signals. The radio signal aided in gaining more information on detecting at what level of everyday occurrences trigger stress or anxiety in the human body. (Fukazawa et al., 2019) Facial expression recognition software is another way of detecting stress in human facial expressions. Incorporating facial expression recognition software is an excellent tool. This framework uses audio-visual hardware and techniques to collect data.

The software application must be capable of using “affective computing” which can be defined as computers that are able to recognize, interpret, and simulate the effects of stress. The way this works is to effectively design Human-Computer interaction or HCI with a more natural feel or effect. This gives the computer the ability or ability to recognize and interpret facial expressions as a human does. (Tawari & Trivedi, 2013). The first detection or realization that someone is stressed or experiencing anxiety is by looking at someone’s facial expressions. These facial expressions will show while at work, driving, or in conversation with someone on the phone or in person.

Facial expression recognition software has proven in simulation that this is especially useful when detecting when a person’s anxiety has been triggered or their stress levels have increased. (Tawari & Trivedi, 2013) Gaining a basic understanding of the six basic emotions which a human will express aids in determining when stress kicks in. The six basic emotions are Happy, Sad, Surprise, Fear, Anger, and Disgust. Testing has shown that when in simulated environments using video cameras along with facial expression recognition software these basic human emotions can be seen and detected very well. (Tawari & Trivedi, 2013)

Challenges discovered when trying to track and analyze facial expressions using video are dealing with the changes in the shape of the mouth during each emotion. It was proposed during the study that only focusing on the upper portion of the face during the silent phase of testing eliminates the distraction of the mouth changes. Further testing and analysis of results show that full-face simulation yields the best results for showing varying emotions of the human face. (Tawari & Trivedi, 2013) To determine at what point elevated levels of stress affect someone’s work performance and how much stress affects an employee’s alertness and safety, specific testing was done.

Normally people rely heavily on computers to aid in their workday responsibilities. Studies have shown that using a computer for a prolonged time is responsible for computer-related physical and mental stress symptoms. Also, the type of job responsibilities plays a key role in stress as well. For example, the day-to-day job responsibilities of a Cybersecurity Operations Center Analyst or cybersecurity analyst are both known to induce prominent levels of stress while on the job. A study called Affective Computing has been introduced. Affective Computing is studying the influences of simulated stressful conditions. From this study, the computer is trained to simulate and recognize stress in human activity. (Akhonda, et al., 2014) Previous studies using affective computing or human-computer interaction only studied situations of computer use during short periods of time such as game playing which was not practical for serious studies of stress. Also, other studies paid little attention to how stress affected the mental and physical health of prolonged computer use or stressful workday situations. (Akhonda, et al., 2014)

The goal of this study was to determine the stress level during a prolonged stressful event such as an overly busy workday. The biosensors used in this study were the ECG, EMG, EOG, and EEG. Each biosensor provides valuable information about different critical areas of the body. The electrocardiogram (ECG) is one of the simplest and fastest tests used to evaluate the heart. The Electromyography (EMG) sensor measures muscle response or electrical activity in response to a nerve's stimulation of the muscle. The test is also used to help detect neuromuscular abnormalities. The electrooculogram (EOG) is an electrophysiologic test that measures the existing resting electrical potential between the cornea and Bruch's membrane. And the Electroencephalogram is a test that detects abnormalities in your brain waves, or in the electrical activity of your brain. (Akhonda, et al., 2014)

In the end, the goal of an effective computing system is to properly detect elevated levels or dangerous levels of stress during the workday. Specifically, the workday of a cybersecurity operations center employee's day. The effective computing system will effectively allow the computer to be intelligent enough to communicate or alert the user when their users when prominent levels of stress have been detected as well as issue messaging and alerts to take a break and step away from the computer. (Akhonda, et al., 2014)

Medical studies have shown that stress and anxiety in the workplace are detrimental to not only the employee but to the company as well. Multiple tests and analyses of prolonged stress levels have been shown to reduce human life expectancy by three years. So, improving, motivating, and uplifting employees and allowing flexibility is not only healthy for the employee but also critical to occupational safety, well-being, and productivity. (Zenonos et al., 2016)

Employees in Cybersecurity Operations Centers are the "First Responders" so to speak when it comes to the defense of internet attacks and intrusions. They are the core and strategy of the operation centers. This is an incredibly stressful career choice. What we hope is that these employees are stress-free and free of distractions. The reality is that there is a shortage of these workers with this especially important skill set and not only is there a shortage, but this job is stressful with a huge responsibility. (Hull, 2017) In recent studies investigating the human factors in the careers of cyber defense are focused on situation awareness, cognitive ability, and cyber defense analyst training. Additionally, the question that often arises is if cyber-attacks affect the stress level of the analyst. Furthermore, another question is how to moderate and offer solutions for rising stress levels for these types of employees. There are plenty of studies on the stress impact of Air Traffic controllers and call centers, but since the new profession of cybersecurity, there are not many studies or specific studies on stress detection on cyber security operators.

The few studies that have been done show that there is a “perfect storm” brewing within these cybersecurity operating centers. The combination of complex tasks and high-level security operations can lead to human burnout, fatigue, human error, and decreased job performance.

Another definition of cybersecurity can be described as a mission-critical service for the safety of digital information of companies, organizations, schools, universities, and government entities. These critical missions include day-to-day real-time defense monitoring and threats to digital networks. (Operations, et al, 1994) The relationship between high-risk working environments and elevated levels of stress and burnout can be a concept that goes together. In other words, you cannot have one situation without the other.

The mental exhaustion that comes with working in a high-risk environment can be detrimental to cybersecurity and dangerous for the employee’s overall health and well-being. The goal of this study is to gain a deeper understanding of the human factors that go with being in cyber operations. (Operations, et al, 1994) Job stress comes with the territory of being a cybersecurity professional. The definition of job stress can be stated as work demands beyond the scope of the employee’s knowledge and ability. Or it can be described as more demands and job responsibilities than one person can manage during one workday. (Cho, Yoo, & Lim, 2020) With the intensity of being a cybersecurity professional while monitoring, tracking, and protecting companies or government entities’ confidential information day in and day out can result in anxiety and burnout quickly.

Studies have shown that employees may become dissatisfied with their jobs. When an employee becomes dissatisfied with their jobs or job responsibilities then job performance is affected.

RELATED METHODOLOGY

Human emotions are mostly affected by stressful environments such as work, the commute to work, home life, and unhealthy relationships. These everyday life incidents are something everyone experiences. These events are called psychophysiological occurrences. Stress can be described as a complex emotional state that can be detected by biomedical methods, self-report surveys, and biomarkers. However, these methods are not useful for real-time data capturing. (Xu et al., 2022) Stressful triggers and daily routines are only two experiences that affect human daily routines. There are many others such as feelings, bodily changes, cognitive reactions, behavior, and thoughts. To monitor and analyze these emotions with technology is called Human-Computer Interaction (HCI) technique.

This technique is very challenging because everyone is different, everyone has different stressful triggers, and people live in different environments which may be stressful to some and not at all to others. (Agrafioti, et al, 2012) The difficulties in designing research for emotion detection lie in finding reliable and meaningful data. It is problematic to design just one experiment to detect many different emotions and cumbersome to design many different experiments to detect one emotion. Again, people are different, and people will respond differently when exposed to the same stimuli, there are varying moods and the inability to accurately self-report an emotional experience. (Agrafioti, et al, 2012)

Related research has been found on stress detection using Affective Computing. Affective Computing has increasingly become a topic of interest as more people become aware of how their physical health is related to their emotional health, and how technology correlates with them both. (Greene, et al., 2016) Steady growth has been seen in studies not only in software technology but hardware technology as well.

This growth has pointed more toward the study of how to detect someone's emotional or mental state and analyze the data. (Greene, et al., 2016) The research focuses on Human-Computer Interfaces (HCI), a modern form of computer science because it ties human emotional detection to technology. (Greene, et al., 2016) Affective computing recognizes a psychophysiological state that influences behavior which in turn affects human emotion that is shown on the face in various emotional states. The six basic emotional states are joy, anger, surprise, disgust, sadness, and fear. (Greene, et al, 2016) "Psychophysiology is the study of the relationship between physiological signals recorded from the body and brain to mental processes and disorders. These biological signals may be generated by the activity of organs in the body or by muscle activity." (O'Donnell & Hetrick, 2016)

There are four basic negative emotions when defining stress. The negative emotions are anger, disgust, sadness, and fear. There are only two positive emotions that are stress related which are surprise and happiness. During the testing state, using a trained model set, the participant is shown an image. If the participant is shown as being disgusted or angered, then it is considered to have instantaneous psychological stress detection. (Xu et al., 2022)

The technologies used to detect these physiological signals are the following: (Greene, et al, 2016)

- Brain activity – Electroencephalography (EEG)
- Heart activity – electrocardiography (ECG)
- Skin response – galvanic skin response (GSR) and Electrodermal activity (EDA)
- Blood activity – photoplethysmography (PPG)

- Muscle activity – electromyography (EMG)
- Respiratory response – piezoelectricity/electromagnetic generation

The technologies used to detect these physical signals are the following: (Greene, et al, 2016)

- Facial expression – automated facial expression analysis (AFEA)
- Eye activity – infrared (IR) eye tracking
- Body gesture – automated gesture analysis (leveraging AFEA)

Mostly, stress is caused by everyday tasks or routines which is called acute. Then there are the chronic stressors of life. These triggers that cause chronic stress are things that happen out of the ordinary, such as unexpected expenses, health emergencies, possible additional tasks or errands added to an already packed schedule, or maybe learning a new language, or having to take a test. All these stressful triggers can cause chronic health conditions if left unmanaged or untreated. Additionally, stress that comes from working inside such as the typical eight-hour shift, sitting in an office or cubicle, looking at the computer screen, and answering telephone calls, or emails is called "Office-Syndrome". The study on this stressful environment is called Office-Syndrome detection using EEG, and HRV, as well as measuring hand movement. (Reanaree, et al, 2016)

The methods used in detecting Office-Syndrome are measured by a specially made watch. The watch uses the Microcontroller AtMega 328 cortex MO as the main processor. And to measure the roll and pitch orientation of the wrist, the Accelerometer ADXL345 is used. For further detail and analysis of the data captured from the roll and pitch of the wrist, the data is stored separately. (Reanaree, et al, 2016)

For additional stress detection, a heart rate sensor called the Neurosky Mindwave, a commercial EEG device used inside a wearable device such as a watch, is highly reliable in capturing data for stress detection. The Neurosky Mindwake device detects stress during increased heart activity and captures data during resting states. Resting states can also be used as a benchmark on individuals, since everyone is different, this information is very useful. The algorithms used for hand movement and stress detection are similar in this study. If there is hand movement, a score is given.

Simultaneously, if stress is detected by increasing heart rate activity, then another score is given, which ultimately increases the total score for the final analysis. (Reanaree, et al, 2016) Methodologies are needed to detect this type of stress and its urgency to heighten awareness. There are many stress and emotional state detection methods available. Many of these methods are invasive and time-consuming to collect relevant data needed to make individual health assessments. More research and study are needed to automatically detect stress, collect data, analyze the data, and send recommendations for treatment all in real-time. To aid in capturing or identifying stress, studies have shown that using video cameras and audio recorders has been impressive and reliable. Additionally, wearable devices have been proven to be convenient and successful in capturing large amounts of data for further analysis.

Questionnaires are an option to gather data on test participants' current mental states, sometimes people are not entirely truthful when completing the surveys. Moreover, wearable devices not only offer convenience but also capture multiple signals. The signals that can be captured with wearable devices are physiological signals using microelectromechanical systems (MEMS). These systems are Electrodermal activity (EDA), Photoplethysmography (PPG), and acceleration sensors which all measure the physiological signs of stress.

Studies have shown that using wearable devices to detect stress by capturing electrodermal activity (EDA) and heart rate (HR) activity successfully shows the physiological signals when stress is triggered. (Reanaree, et al, 2016) The ability to detect stress using a wearable Photoplethysmography sensor using Heart Rate Variability data is a more recent study. This study has proven to have reliable results in detecting stress as well.

This method uses a five-step process. As described by medical doctors, the heart beats using two natural pacemakers which are connected to the body's nervous system. So, if there are any changes happening in the nervous system it will ultimately affect the heart. The five-step process in how to get good HRV parameters is as follows:

- Extract B2B (beat to beat) data from heart rate data.
- Define frequency zones.
- Perform a Periodogram of those frequency zones.
- Find the area under the curve of the frequency zones.
- Calculate LF/HF values (Mohan & Nagarajan, 2016)

Among the available stress detection methods are monitoring heart activity, brain activity, skin conductance, blood activity, and muscle activity. All these methods are referred to as physiological stress-based Affective Computing. (Greene, Thapliyal, & Caban-Holt, 2016) An additional physiological stress indicator is the biomarker of Salivary Cortisol. The "Stress Hormone" or Cortisol has been studied for many years. Researchers have measured the increase in cortisol levels in individuals that have shown high-stress levels or after the stress has been triggered.

The study of the increase in cortisol levels has been a successful indicator of stress in study after study. (Reanaree, et al, 2016) Studies have successfully shown that physiological signals can identify human emotions. This has been done by combining the electromyography (EMG), the ECG and the galvanic skin response (GSR) to detect stress in operating cars. The ECG has proven to be a reliable source of stress detection data in human emotion recognition systems.

There are several machine learning techniques used to analyze the data extracted from the ECG. Data from the ECG sensor combined with data extracted from the Heart Rate Variability (HRV) are successful in establishing an emotion recognition system. To correctly identify and label the various emotions, different physiological signals are analyzed. The signals are captured from the Electroencephalography (ECG) which is brain activity, electromyography (EMG) which is muscle activity, respiration, and skin conductivity. A multi-model database was established, named DREAMER. This database uses ECG signals to help determine emotions triggered from audio-visual stimulation. In this study other databases are created using neurophysiological signals to detect human emotions. The AMIGOS database is used to capture personality traits.

This study also proposed to use an augmentation using ECG data for recognition of human emotions using a seven-layer convolutional neural network (CNN) model. To accomplish the task of recognizing human emotion and using imbalanced samples used in Machine Learning approaches, the steps are detailed as follows:

- Describing the augmentation strategy
- Detecting the R-waves
- Periods Calculation of R-R intervals – There are different periods between successive R-waves (R-R intervals)

- Random selection of new R-R intervals
- R-R intervals concatenation. (Nita, et al, 2022)

Basic concepts and motivation are established by studying the following steps:

- Human emotion
- ECG and emotion recognition
- Emotion detection methods
- ECG-based emotion detection methods
- EEG-based emotion detection methods. (Nita, et al, 2022)

Detecting human emotions is extremely difficult, not only are human emotions a psychological activity, but also a complex series of behavioral emotions, classified as a phenomenon.

These behavioral emotions involve various levels of neural and chemical interactions. To properly recognize human emotions, three main qualities must be described. The qualities are:

- **Valence:** positive or negative emotion such as fear or happiness
- **Arousal:** an intense or extreme emotion such as anger or sadness
- **Dominance:** the level of control either with control or without control.

In ECG and emotion recognition, the heart rate can be defined as the number of beats per minute which is the systolic contraction. Simultaneously, the ECG is recording the electric cardiac activity which is responsible the myocardial contraction.

Myocardial contraction is the heart's natural ability to contract. Additionally, the heart rate is measured by counting the number of R waves that are registered by the minute. And the time or interval between two electrical R waves is labeled as the R-R interval. (Nita, et al, 2022)

In previous studies, it has been determined that the most important way to recognize human emotions is by analyzing data that was captured from ECG sensors. Specifically, a study was done to determine the human emotional response when listening to music. Not only was the ECG sensor used, additionally the ECG, EMG, respiration, and skin conductivity sensors were used in this study as well. Calculations were made from HRV/Breathing rate variability (BRV), geometric analysis, entropy, multiscale entropy, time/frequency, and sub-band spectra. All of these were included in the analysis to detect the best human emotion while listening to music. Moreover, studies have shown that the EEG provides important insight into the complex information about an individual's emotional state. However, existing methods are unable to accurately determine the exact human emotion. (Nita, et al, 2022)

Furthermore, physical stress-based Affective Computing includes the following methods: facial features, eye tracking, body movements, and gesturing. To accurately detect heart activity is to collect data from the Heart Rate (HR) and Heart Rate Variability (HRV) using electrocardiography (ECG). Electrocardiography (ECG) captures the activity of the heart by measuring the heartbeat. The heartbeat consists of four components. These four components are the baseline, P wave, QRS complex, and T wave. The HRV provides more information alone than the HR. "The Heart Rate Variability is the measure of the standard deviation in interbeat intervals of successive R waves in a single Heartbeat." (Greene, et al, 2016) Studies have also shown that the temperature of the skin changes considerably during increased stress levels.

The sympathetic nervous system triggers short-term temperature changes in the skin when someone is under stress or in a prolonged stressful environment. (Reanaree, et al 2016) Normally, when someone is in an active stressful state, their bodies give the signal to speed up the Heart Rate (HR). This signal is to speed up the HR which also increases the blood supply throughout the body, this also gives the alert to go into “fight-or-flight” mode. The “fight-or-flight” mode is very common in urgent situations where someone may have to make quick decisions in possibly, life, or death situations. The most widely used in stress detection to date is the ECG, which uses electrodes that are placed on specific areas of the body.

Even though this is somewhat of an intrusive process and cumbersome with placing each electrode on the body, the data captured is accurate in detecting stress in the body by analyzing the heart rate and the heart rate variability. One of the few companies that manufactures ECG recording systems is called Biopac Systems, Inc. and the software that is used to capture offline and online, real-time analysis is called AcqKnowledge. Its competitor Shimmer Sensing offers a wireless, wearable ECG device.

This allows wireless real-time synchronization and analysis which is preferable to use when trying to detect stress in individuals during their normal or daily routines. (Greene, et al, 2016) Research has shown that a healthcare system designed to focus on emotional aspects to support people in stressful work environments and daily life has been successful. This study showed the health care system proved to be effective when used in conjunction with the ECG signal because stress is one of the mental problems or symptoms. (Tivatansakul & Ohkura, 2015) Brain activity, which is the center of all activity in the body is normally captured using an Electroencephalography (EEG). The difference between the EEG and ECG is that the ECG detects stress by capturing electrical impulses in the body.

Whereas the EEG detects stress by measuring blood flow as an indicator. (Greene, et al, 2016) There has been an increase in research on using skin conductance as an indicator of stress. The stress is captured using a Galvanic Skin Response (GSR) sensor. The GSR sensor analyzes the conductivity of skin when triggered in stressful environments. These sensors are becoming more popular because of the less intrusive way to capture data. The GSR can be worn on the finger, or wrist, or using a specially equipped computer mouse. Stress detection using a GSR is proving to be reliable as it relies on the conductivity of the skin response based on stress triggers and stimuli. The skin response is called the tonic skin response.

This stress detection technique is slowly becoming more popular because of its convenience and ease of use. The requirement of the setup is significantly lower than the EEG or ECG testing. Monitoring blood activity is another way to detect stress with the change in the Heart Rate and Heart Rate Variability. It is also a change in the blood pressure and Blood Volume Pulse (BVP). The process of monitoring blood activity uses photoplethysmography (PPG), this technique is very low cost as well as being a noninvasive or non-intrusive process.

The PPG sensor uses an Optical pulse generated by a red or near-infrared (NIR) light source. (Greene, et al, 2016) The most popular and validated technology that uses the PPG is Empatica's E3 and E4 wristbands. These wristbands are GSR sensors that can be worn conveniently on the wrist. There is another up-and-coming company by the name of Seraphim Sense, they are in the process of developing an Angel Sensor health bracelet. This bracelet has many sensors incorporated within the bracelet to detect and capture data from the skin, blood activity, and blood pressure. Additional studies have shown that using the galvanic skin response (GSR) sensor data is useful in detecting stress patterns but can also be problematic at the same time.

Collecting GSR data is not as simple as other studies have described. To detect stress patterns, specific symptoms need to be in place. These symptoms are elevation of the voice, an increase in heart rate in addition to the galvanic skin response (GSR).

This study attempts to detect stress in a two-step process. Step one is identifying the type of stress. Stress can be broken down further into three separate categories. (1) Acute stress. Acute stress is a short-term trigger or stress factor. (2) Episodic acute. Episodic acute stress is the trigger that happens more frequently. (3) Chronic. Chronic stress is described as a long-term stress environment or continuous stressful experience. Step two is the analysis of results captured from the GSR sensor while determining what stage of stress a person is in. (Bakker, et al., 2011)

Muscle activity is another physiological measure of stress. Previous studies have shown that muscle activity or action can be used to identify a response to stress. The technology that monitors muscle activity is electromyography (EMG).

The EMG is like the EEG and ECG in that it uses electrodes placed strategically on the body to detect the spikes as the muscles respond to stress. (Greene, et al, 2016) This detection technique is not a good source as it is based on the muscle tone of the participant. The respiratory response is another method to detect stress. The respiratory response uses the technology of piezoelectricity/electromagnetic generation in the detection of stress. Ventilation and Hyperventilation have been shown to be linked to stress because of mental and physical triggers. To capture data from the respiratory response by placing Piezoelectric transducer electromagnetics around the chest area to analyze motion as the chest expands and contracts. This provides an electrical response to the physical changes as the chest expands and contracts based on stress triggers. (Greene, et al, 2016)

Physical stress-based Affective Computing includes facial-related features, eye activity, and body gestures. Facial expression recognition study has proven effective in detecting various emotional states. The technology used to detect these facial expressions is the automated facial expression analysis (AFEA) algorithm. This technology has been used in previous studies to detect sadness, anger, happiness, and deceit. (Greene, et al, 2016) Automated facial expression analysis can be used in conjunction with the Facial Action Code System (FACS). The FACS was first published by Paul Ekman and Wallace Friesen in 1978 and later updated in 1992 and again in 2002. The Facial Action Code System measures the frequency of each facial expression. Each facial expression is then reduced to an action unit (AU). The action units are the smallest possible movements of each facial expression. The AU works effectively with facial expression recognition software applications as successfully detects emotional states based on facial expressions.

The AFEA and FACS together have proven stress and emotional state detection with 93% accuracy. (Greene, et al, 2016) Eye Tracking such as pupil dilation and blink rate has been shown as a positive and reliable detection of stress. The technology used with Eye Tracking is an infrared (IR) eye-tracking system. Using the infrared eye tracking system has shown that as stress is triggered the blink rate increases positively. Additionally, pupil dilation has been proven to be a reliable source of stress detection. There are two eye-tracking systems that are very popular in detecting stress for study. These systems are the Tobi X120 series and the Eye Tribe ET1000 eye trackers. Studies using these Affective Computing systems have shown that the Tobi X120 extracts valuable data from eye activity. This system also offers wearable eye tracker devices which have proven to be convenient and reliable. (Greene, et al., 2016) Wireless Body Sensor Network is a study shown to be able to detect stress in real time. This device is comprised of a self-configuring network of small biosensor nodes all communicating using radio signals.

For real-time stress detection using multiple vital signs is proposed in this study. The framework used for real-time detection is the Wireless Body Sensor Network (WBSN) along with a fuzzy inference system (FIS). This framework will capture data and analyze the data from the skin conductance (SC) first.

Next, if there are signs of stress in the skin conductance data, then the vital signs are captured for further analysis. The vital signs used are the Heart Rate (HR), Respiration Rate (RR), and Systolic Blood Pressure (ABPSys). Studies have shown that these vital signs show the most signs of stress and are mostly affected. (Koussaifi, Habib, & Makhoul, Apr 2018) Behavior and body gesturing are other emerging stress detection techniques, but mostly used in studying individuals with Autism. The technology used in the detection of stress using body gesturing is automated gesture analysis (leveraging AFEA).

This technique monitors body movements such as making a fist, jaw clenching, body stiffness, crossing of the arms, pacing, jittering, and other nervous gestures. conjunction with visual tools that are used to detect facial features which can be a reliable source in determining stress levels and emotional states. (Greene, et al, 2016) The predictive analysis technique is an additional method used in stress detection. This technique is used in research on drowsiness detection, Pulse Rate Detection, and Pulse Monitoring Systems. Drowsiness is an overlooked system of unmanaged stress. When designing new stress detection technology, it is important to include eye drowsiness detection. Also, a Pulse Rate Detection system has been shown in research to be an effective technique. This technique is used in conjunction with heart rate and heart rate variability monitoring. Lastly, a Pulse Monitoring System uses the Thing Speak Software for transferring the pulse rate values detected in real-time.

This gives a positive representation of the stress levels of an individual so stress can be properly assessed. (Sengupta, 2021) The workflow or the best practices in stress detection and to offer resolution is to first detect the emotion and to recognize what is going on. If a participant is experiencing a series of negative emotions or stress, the next step is to offer a relaxing resolution. The resolution should include a relaxing deep breathing or breathing control technique. The next step should be reanalyzing the stress level in the participant. Then have them redo the breathing techniques. Studies show that integration of stress detection with ECG technologies proves to positively detect stress and improve the efficiency of emotional support. (Tivatansakul & Ohkura, 2015)

There hasn't been much research done on multi-model stress detection. A few recent studies show that systems that do use multi-model emotion detection systems such as combining audio signals and visual signals seem to cause dimensionality and cause data sparseness. Additionally, not much work has been done on combining EEG, Emotion Tracking, and Speech Emotion Recognition. This may prove to be essential in Human-Computer Interaction. (Danai & Moschona, 2020)

MULTI-MODEL METHODOLOGIES

A few studies have shown that using a combination of different emotion and facial recognition detection methods has proven to show a higher accuracy rate. The high accuracy rates mean that using a multi-model approach can more accurately detect very specific emotions. Pinpointing a single emotion can mean the difference between someone making a catastrophic mistake on the job or calming an individual down in the middle of a stress trigger in real-time.

Combining detection methods such as using a multi-model database in conjunction with an EEG sensor and speech signals is called Fusion strategies. In this study, using Fusion methods which combines speech and EEG signals should improve accuracy ratings by twenty-five percent. It is very important with Human-Machine Interaction (HMI) to also have an Automatic Emotion Recognition system in place. (Wang, Wang, Yang, & Zhang, 2022)

External behaviors that can be detected are body movements and gesturing as well as the tone of someone's voice. In this study, a multi-model emotion database was built using four different methods. The methods consisted of recording the signals of an EEG sensor, photoplethysmography, speech, and facial expressions at the same time from thirty-two different experiment participants. The results showed that the EEG signals gave an 88.9% higher accuracy rating than speech recognition alone. This study also showed that by combining emotional external behaviors and internal physiological behaviors proved to recognize human emotions. (Wang, et al., 2022)

Additionally, this study presents that humans can hide emotions intentionally or involuntarily, which is known as social masking. Research proves that using signals from Automatic Nervous System (ANS) and Central Nervous System (CNS) such as from the EEG is not easily concealed. (Wang, et al., 2022)

To detect, determine, and analyze these emotions a high-level functionality and purpose must be created. To classify each emotion the Python coding application is used in this study. Python uses an Emotion Classification tool to train, evaluate, and deploy machine learning models to detect emotion. (Alvarez-Gonzalez, et al., 2021) To retrieve the best analysis the functionality is split between two programs in Python:

- Run.py: which is a single argument program that executes an experiment configuration.
- Serve.py: this is a webserver that exposes release-ready research models. (Alvarez-Gonzalez, et al., 2021)
- This study showed that the collection of an Open-Sourced tool named Emotion Core was successfully used to train, evaluate, deploy, and showcase the various ways emotion can be detected using a variety of modeling techniques, datasets, and approaches to evaluations. (Alvarez-Gonzalez, et al., 2021)
- The impact of this research using Emotion-Core allowed researchers to experiment with various detection methods, data sets, document representation, and modeling approaches at a very fast pace. The experiment methods included:
    - Data formats: In Emotion-Core there are only two columns needed:
        - Test
        - Emotion index
    - The researcher conducted the experiment and preprocessed the columns accordingly.
    - Document Representation and Models: This allows for definitions to be centralized of how to train and represent a model. (Alvarez-Gonzalez, et al., 2021)

Recent studies have shown that during various emotions, these activities occur in different areas of the lobes within the brain. During these various emotions, activities in the brain either fire up or fire down in different regions of the brain. Literature and research cannot be overlooked, that these phenomena in the brain are asymmetric. (Gannouni, et al, 2022) However, there is very little research done or published on EEG-based emotion recognition using asymmetric brain activity. There is plenty of published work done on emotion detection using other methods, but not multi-model detection or asymmetric studies. Most studies show that studying emotions used only a fixed set of electrodes when using EEG-based detection. This study shows that based on scientific findings in neuroscience, for every subject and for every emotional state there are a set of appropriate electrodes that match that frequency. (Gannouni, et al, 2022)

Introduced in this article were different methods of determining and recognizing emotions through EEG brain analysis. There were three different classifications identified and their accuracy ratings were between 88.17% and 100%. The three phases of the classification strategy were created and used to determine nine different emotional states. The phases are as follows:

- Phase 1- Two classifiers were created to determine two different emotional states using the QDC classifier.
- Phase 2 – ensemble classifiers were defined as having the same emotional target.
- Phase 3 – decisions were made based on the analysis of phases one and two. The accuracy level was between 77.21% and 99.48%. (Gannouni, et al, 2022)

There are many studies currently being done on facial recognition, identification of emotions, and detecting of stress. However, the problem is that the accuracy levels of the testing have not been good.

Even though research methods are improving the results have been less promising. To properly detect stress, first facial recognition and emotional analysis must be established. Currently, there are three methods of research to detect and analyze facial expressions. (Piwowarski & Wlekły, 2022) These methods are:

- fEMG – facial electromyography- this is the measurement of facial electromyographic activity.
- Having human coders analyze facial expressions in real-time observations.
- Using video and cameras to record and capture the various changes of expressions by classification algorithms. (Piwowarski & Wlekły, 2022)

Facial electromyography (fEMG) is basically placing electrodes on the face to collect impulses and to directly measure the muscle activity of the face. These signals are processed, filtered, and then converted into digital format for further analysis. The electrodes are placed on two major muscles on the left side and right side of the face.

The advantage of this method of measurement is that it is very precise, sensitive, continuous, and consistent. The disadvantage is that for the testing to be done, the electrodes must be placed correctly along with the cables, amplifying device, and other equipment. (Piwowarski & Wlekły, 2022) The Facial Action Coding System (FACS) is the method of observing and analyzing facial expressions in real-time. The coding system is based on the recognition of facial movements based on an anatomical, accurate structure of the face.

The encoding is measured in Action Units (AU). The action units are described in numbers, names, and activated muscles by groups. (Piwowarski & Wlekły, 2022) Lastly, the Automated Facial Expression Analysis (AFEA) enhances the process of facial expression recognition.

However, it is not a simple process because of the variance of human faces. Faces vary based on gender, ethnicity, age, facial hair, glasses, and even the lighting can all influence the recognition of facial expressions. There are three distinct stages of automated analysis of facial expressions. The three stages are:

- Face detection
- Detecting and registering facial landmarks
- Classifications of facial expressions and emotions. (Piwowarski & Wlekły, 2022)

Multi-model facial expression detection studies are becoming more popular but have proven to be unreliable. More research is needed to make these detection methods more reliable and trustworthy. The multi-model methods include combining facial expressions analysis, voice recognition, and gesture recognition.

To get more accurate results an EEG sensor must be added. The reasoning behind using EEG readings is that the results remain unaffected by external appearances and behaviors. (Joshi & Ghongade, 2021) Generally, EEG signals are generated from different sections of the brain. To get accurate results the testing uses the analysis from the EEG using the Spatio-temporal brain data (STBD). This method uses the data from STBD by recording the activity of the neurons evoked from the brain. The approach used to collect STBD data is the testing method of subject contingent and subject noncontingent. (Joshi & Ghongade, 2021) In this study, two methodologies were proposed. The methodologies were:

- To develop a training model and a feature extractor. This method improves the classification performance of emotion detection.
- To examine the model proposal using the theta, alpha, beta, and gamma band. (Joshi & Ghongade, 2021)

The datasets used with the above methodologies were:

- DEAP – the database was created using EEG recordings collected from 32 participants (16 females and 16 males).
- SEED – database was created at the Brain-Like Computing and Machine Intelligence Laboratory (BCMI). (Joshi & Ghongade, 2021)

The extraction feature uses the EEG signal. Studies have shown that the EEG signals from emotions play a critical role in designing the Human Brain-computer Interface. Six features were used for the evaluation of emotional performance. The Six features were:

- Hjorth parameters – Statistical properties used for time-domain analysis in processing the signal.
- Power Spectral density (PSD) -The average energy distribution per unit of time over different frequency bands.
- Differential entropy (D_fE) - is the Differential entropy h(X) of a continuous random variable X.
- Rational asymmetry (RASM)- the formula is:
    - $RASM = h(X_1^{left}) – h(X_1^{right})$

- Differential asymmetry (DASM) – the formula is:
    - DASM = $h(X_1^{left}) - h(X_1^{right})$
- Linear Formulation of Differential Entropy (LF-D_fE)- this is based on the fourth-order spectral moment. (Joshi & Ghongade, 2021)

ADDITIONAL MIXED MULTI-MODEL METHODOLOGIES

Recent studies have shown that automatic response recognition between humans and computers could be more of a natural occurrence if computers understood nonverbal cues or behavior from humans. Automatic response recognition has peaked the attention of artificial intelligence researchers as recently as within the last decade. Body movements, gestures, and facial expressions are all considered nonverbal cues that express human emotions. Additionally, until recently research on affective computing has only been done on a single chann s to include, speech, facial expression, gesture, and gaze all while occurring together. (Gunes & Piccardi, 2007)

The process of integrating multiple methods of expression recognition is mostly motivated by human-to-human interaction (HHI). During a normal conversation or human-to-human interaction, communication is normally done by multiple methods. The methods include language (talking), tone of voice, facial expression, gestures, and movement of the head are all done during el or mode of information. Studies more recently have increased using multi-model methodologie

normal conversation. (Gunes & Piccardi, 2007)

The method in which the research is done initially focuses on facial expressions and body gestures separately. The task is to analyze cues captured within Human-to-Human Interaction (HHI) and then Human to Computer Interaction (HCI).

This analysis is usually done while in a sitting position, so the focus remains on the upper portion of the body, such as the shoulder area, head, and face. The assumption is the participants are facing each other while communicating, with the upper body, two hands, and face visible. Testing modalities are as follows: (Gunes & Piccardi, 2007)

EXPERIMENTAL DESIGN APPROACH

My approach is to review all possible literature on previous studies and work on the topic of stress detection and management for Cybersecurity analysts to see what has already been done. The next steps are to attempt to recreate, compare, and contrast the successful, unsuccessful, and related work. Analyzing the test results from the experiment to what is needed and how to move in a different direction. After the recreation of previous experimentations is done, the next steps will be to incorporate different sensors, datasets, and simulations to try and receive different and possibly better results for better accuracy in detecting stress.

The Setup/Experimental Design:

To properly detect stress in an experimental setup, is first to set up a lab for audio, visual, and sensor data collection. The equipment initially needed are high-definition cameras, computer workstations with a facial expression recognition application installed along with coding software such as Python. The facial expression recognition software will work in conjunction with the high-definition cameras to capture each emotion. Facial expression recognition software is used to recognize human expressions on a person's face. This method has been shown to be highly effective in detecting stress. (Shaul Hammed et al., 2020) Each emotion will be captured, coded, and analyzed for the study of stressful triggers. Test participants will be shown various computerized scenarios to include humorous, disturbing, emotional, action or high-paced, or maybe even a visual of something disgusting.

Each scenario will be specially designed to trigger specific each one of the six basic emotions. First facial recognition and emotional analysis must be established. Currently, there are three methods of research to detect and analyze facial expressions. (Piwowarski & Wlekły, 2022) These methods are:

- fEMG – facial electromyography- this is the measurement of facial electromyographic activity.
- Having human coders analyze facial expressions in real-time observations.
- Using video and cameras to record and capture the various changes of expressions by classification algorithms. (Piwowarski & Wlekły, 2022)

Facial electromyography (fEMG) is basically placing electrodes on the face to collect impulses and to directly measure the muscle activity of the face. These signals are processed, filtered, and then converted into digital format for further analysis. The electrodes are placed on two major muscles on the left side and right side of the face. To aid in capturing or identifying stress, studies have shown that using video cameras and audio recorders has been impressive and reliable. Additionally, wearable devices have been proven to be convenient and successful in capturing large amounts of data for further analysis. Moreover, wearable devices not only offer convenience but also capture multiple signals.

Questionnaires are an option to gather data on test participants' current mental states, sometimes people are not entirely truthful when completing the surveys. Among the available stress detection methods are monitoring heart activity, brain activity, skin conductance, blood activity, and muscle activity. All these methods are referred to as physiological stress-based Affective Computing. (Greene, et al., 2016)

The signals are captured from Electroencephalography (ECG) which is brain activity, and electromyography (EMG) which is muscle activity, respiration, and skin conductivity. A multi-model database was established, named DREAMER.

This database uses ECG signals to help determine emotions triggered by audio-visual stimulation. In this study, other databases are created using neurophysiological signals to detect human emotions. The AMIGOS database is used to capture personality traits. This study also proposed to use an augmentation using ECG data for the recognition of human emotions using a seven-layer convolutional neural network (CNN) model.

Basic concepts and motivation are established by studying the following steps:

- Human emotion
- ECG and emotion recognition
- Emotion detection methods
- ECG-based emotion detection methods
- EEG-based emotion detection methods. (Nita, et al., 2022)

Detecting human emotions is extremely difficult, not only are human emotions a psychological activity, but also a complex series of behavioral emotions, classified as a phenomenon. These behavioral emotions involve various levels of neural and chemical interactions. To properly recognize human emotions, three main qualities must be described. The qualities are:

- **Valence:** positive or negative emotion such as fear or happiness

- **Arousal:** an intense or extreme emotion such as anger or sadness
- **Dominance:** the level of control either with control or without control.

Wearable ECG:

In ECG and emotion recognition, the heart rate can be defined as the number of beats per minute which is the systolic contraction. Simultaneously, the ECG is recording the electric cardiac activity which is responsible the myocardial contraction. Myocardial contraction is the heart's natural ability to contract. Additionally, the heart rate is measured by counting the number R waves that are registered by the minute. And the time or interval between two electrical R waves is labeled as the R-R interval. (Nita, et al., 2022)

Even though this is somewhat of an intrusive process and cumbersome with placing each electrode on the body, the data captured is accurate in detecting stress in the body by analyzing the heart rate and the heart rate variability. One of the few companies that manufactures ECG recording systems is called Biopac Systems, Inc. and the software that is used to capture offline and online, real-time analysis is called AcqKnowledge. Its competitor Shimmer Sensing offers a wireless, wearable ECG device.

This allows wireless real-time synchronization and analysis which is preferable to use when trying to detect stress in individuals during their normal or daily routines. (Greene, Thapliyal, & Caban-Holt, 2016) During the testing state, using a trained model set, the participant is shown an image. If the participant is shown as being disgusted or angered, then it is considered to have instantaneous psychological stress detection. (Xu et al., 2022) The technologies used to detect these physiological signals are the following: (Greene, et al., 2016)

- **Brain activity** – Electroencephalography (EEG)

- **Heart activity – electrocardiography (ECG)**
- **Skin response – galvanic skin response (GSR) and Electrodermal activity (EDA)**
- **Blood activity – photoplethysmography (PPG)**
- **Muscle activity – electromyography (EMG)**
- **Respiratory response – piezoelectricity/electromagnetic generation**

The technologies used to detect these physical signals are the following: (Greene, et al., 2016)

- **Facial expression – automated facial expression analysis (AFEA)**
- **Eye activity – infrared (IR) eye tracking**
- **Body gesture – automated gesture analysis (leveraging AFEA)**

To accurately detect heart activity is to collect data from the Heart Rate (HR) and Heart Rate Variability (HRV) using electrocardiography (ECG). Electrocardiography (ECG) captures the activity of the heart by measuring the heartbeat. The heartbeat consists of four components. These four components are the baseline, P wave, QRS complex, and T wave. The HRV provides more information alone than the HR. "The Heart Rate Variability is the measure of the standard deviation in interbeat intervals of successive R waves in a single Heartbeat." (Greene, et al., 2016)

The difference between the EEG and ECG is that the ECG detects stress by capturing electrical impulses in the body. Whereas the EEG detects stress by measuring blood flow as an indicator. (Greene, et al., 2016) There has been an increase in research on using skin conductance as an indicator of stress.

Wearable GSR

Studies have also shown that the temperature of the skin changes considerably during increased stress levels. The sympathetic nervous system triggers short-term temperature changes in the skin when someone is under stress or in a prolonged stressful environment. (Reanaree, et al., 2016) Stress signals can be captured using a Galvanic Skin Response (GSR) sensor. The GSR sensor analyzes the conductivity of skin when triggered in stressful environments. These sensors are becoming more popular because of the less intrusive way to capture data. The GSR can be worn on the finger, or wrist, or using a specially equipped computer mouse. Stress detection using a GSR is proving to be reliable as it relies on the conductivity of the skin response based on stress triggers and stimuli.

The skin response is called the tonic skin response. As previously mentioned, the various methods used to detect stress are using different biosensors that capture data from various parts of the body. Additionally, these stressful situations can be captured and monitored on video cameras set up during simulations of stressful situations. Also described in detail previously are the different biosensors that are used to capture blood pressure, skin resistance, heart rate, brain waves, and muscle responses. All these electric responses also show on the face with different facial expressions. Along with video recording, there will be facial expression recognition software used to analyze each expression.

Again, each of these features will be used to aid employers to detect stress better in their employees during the workday, especially in high-level cybersecurity professions. There are many methods and technologies used to detect stress and emotional stress in individuals. Studies have shown that the most reliable or high accuracy ratings come from using multiple modes and various sensors to capture data. (Greene, et al., 2016)

Studies have also shown that emotions play a critical role in motivation, perception, and decision-making. If emotions are running "high" because of a prolonged stressful situation, the employee may be prone to making a serious mistake or not caring at all about the severity of the situation at hand. (Hosseini & Khalilzadeh, Apr 2010) More studies have shown that Affective Computing is a growing field of technology that can effectively detect stress and various emotional states using multi-model sensors to capture data. (Greene, et al., 2016) The intentions of this literature review are to have done an exhaustive search on all studies done on stress, anxiety, and emotional health and how each left untreated can negatively affect the cybersecurity professionals of our society.

If a participant is experiencing a series of negative emotions or stress, the next step is to offer a relaxing resolution. The resolution should include a relaxing deep breathing or breathing control technique. The next step should be reanalyzing the stress level in the participant. Then have them redo the breathing techniques. Studies show that integration of stress detection with ECG technologies proves to positively detect stress and improve the efficiency of emotional support. (Tivatansakul & Ohkura, 2015)

Methodologies

The importance of these wearable sensors is their placement. The wearable sensor can also be in the form of an intelligent garment such as a t-shirt or gloves. Placement is key in capturing the correct biometric to give correct information.

The sensors need to be placed:

- Chest

- Wrist and hands
- Head
- Ears
- Eyes
- Ankle

My contribution

There are not many studies done on multi-model stress detection. There are a few recent studies that show systems that use multi-model emotion detection systems such as combining audio signals and visual signals but seem to cause less accurate results. Additionally, not much work has been done on combining EEG, Emotion Tracking, and Speech Emotion Recognition. This may prove to be essential in Human-Computer Interaction. (Danai & Moschona, 2020) My goal is to offer more research studies and experimentation using multi-model sensors by capturing data from various electrical activities of the human body.

I would like to show that detecting stress from various parts of the body can better determine how to manage triggers and symptoms of stress. If a participant is experiencing a series of negative emotions or stress, the next step is to offer a relaxing resolution. The resolution should include a relaxing deep breathing or breathing control technique. The next step should be reanalyzing the stress level in the participant. Then have them redo the breathing techniques. Studies show that integration of stress detection with ECG technologies proves to positively detect stress and improve the efficiency of emotional support. (Tivatansakul & Ohkura, 2015)

Studies have also shown repeatedly that stress and anxiety are two forms of physical and psychological tension. These two uncomfortable and dangerous forms of tension in the human body can negatively affect someone's daily work performance. (Widanti, et al., 2015) In the world of cybersecurity, the safety of critical information lies in the hands of these professionals. These studies are aimed to detect stress levels at various levels and learn what exactly triggers stress during various situations.

My proposal is to find a reasonable method for stress management and to offer comfortable resolutions to aid in keeping stress at a minimum during the workday for cybersecurity analysts. Additionally, the employee's health, well-being, and mental state will be positively affected to continue to protect the digital information he or she is protecting from cyber-attacks.

Using various sensors to capture the different biometrics when stress is triggered and incorporating facial recognition software to analyze human emotion is the goal of this study. The various sensors that are currently being studied will be explained individually. Using Smart Bands to monitor stress levels has been shown to be a relatively accurate and less obstructive way to capture biometrics in real time. Smart bands are wearable devices that have been proven to help measure stress as well as reduce stress at the same time.

Previous studies have shown that using wearable devices such as a smart band in real-life environments is reliable in detecting stress from physiological signals in individuals. (Can et al., 2020) The stress detection method proposed in this study is to use commercial brand wearable wristbands or smartwatches. These smart devices are used to alert the user of their stress level in real-time. The advantage of these wearable devices is they do not interrupt the individual's daily routine and are unobtrusive.

The wearable devices have embedded sensors to detect Blood Volume Pressure (BVP), Skin Temperature (ST), and Electrodermal Activity (EDA). (Can et al., 2020)

Modality 1: Facial Expressions

- Visual automatic facial expression recognition studying the six basic prototypical human emotions which are universally recognized are as follows:
  - Anger
  - Disgust
  - Fear
  - Happiness
  - Sadness Surprise (Gunes & Piccardi, 2007)

Modality 2: Body Gestures

- Gestures are usually described as expressive or non-expressive, specific body movements of certain body parts or postures. Expressive movements are defined as follows:
  - A bowed head and dropped shoulders normally mean sadness.

Non-expressive body movements are not coded for this study. (Gunes & Piccardi, 2007)

The process of Facial Expression Recognition Systems (FER) simply goes in the order:

- Signal acquisition
- Pre-Processing

- Extraction of features
- Selection of features
- **Facial Signal Acquisition** – capturing images of still photos and videos of various faces in various states of emotions.
- **Preprocessing of Signals** – studying the facial landmarks which include the following:
    - Nose
    - Corner of the eyebrows
    - Corners of the Mouth which are believed to show the most emotions.
    - Pre-Processing of the landmarks includes:
    - Noise reduction
    - Using filters
    - Face detection
    - Color, size, and enhancement normalization (Shaul Hammed, et, al., 2020)
- **Feature Extractions**
  - The experiments done using the participants captured expressions by using a whole frame sequence extraction method and tracking.
  - Feature extractions – normally when information that is useful has been taken from or extracted from an image.

- Additional feature extractions include:
- Geometric extractions- These extractions can be described as appearance based. These include the shape of the head, positions, and angles of the ears, eyes, nose, and mouth. (Shaul Hammed et al., 2020)
- Corners of the Mouth which are believed to show the most emotions.

- Classification of Signals includes using Deep Learning methods such as:
- Convolutional Neural Network (CNN) – using this classifier puts the images together through a filter in layers and produces a feature map which is integrated into other networks to form the facial expression that can be given in the form of output. (Shaul Hammed, et, al., 2020)

Using an open-source software toolkit called Face Research Toolkit (FaRet) can be a useful resource when studying emotion perception from generated images. A reoccurring problem with using three-dimensional or two-dimensional models is that sometimes the natural appearance of the human face is lost, therefore the perception of the generated emotion is inaccurate. The study of Psychophysics is the study of a relationship between stimuli and perception, quantitatively. The stimulation portion of the study is relatively easy as such we can manipulate outside stimuli to include brightness of light, color, contrast, and frequency of information received.

However, it has been difficult when trying to duplicate stimulating situations to get an accurate perception of the emotion being portrayed on the face. Also, to maintain the natural features of the face when incorporating two- and three-dimensional image manipulation has proven to be equally difficult. (Soto et al., 2019)

Stress monitoring systems are needed too for first responders. When we think of first responders, we naturally think about Emergency Medical Technicians (EMTs), Police, military, and Firemen. Rarely are cybersecurity analysts thought of as first responders. But when the idea is given more thought, that is exactly what our cybersecurity analysts are. They are first responders to all the cyber threats that are detected and thwarted, diffused, or otherwise taken down before it is even a threat. A study has been proposed for an Intelligent Stress Monitoring Assistant. This prototype is proposed to be used by any first responders that are exposed to extreme physical and psychological stress triggers daily, such as emergencies. (Lai et al., 2021)

An additional study was found on a wearable device named EMPATICA E4. The EMPATICA E4 is a wearable device with four embedded sensors, Photoplethysmography (PPG), Electrodermal activity (EDA), a 3-axis accelerometer, and an optical thermometer. The PPG sensor measures the heartbeat volume change with each beat individually. The EDA captures and measures the conductivity of the skin. The thermometer measures light with an optical infrared thermometer. The three-axis accelerometer measures motion. (Aristizabal et al., 2021) For emotion recognition, a tool was used named Weka. Weka is an automatic classification tool used in the separation of each emotional class. During this study, a separate class was created for each emotion, face, and body. Before completion of the experiment, a Bimodal Emotion Recognition is used to integrate all incoming single modalities into a combined single representation.

The main issue with combining the modalities is when exactly is good to combine the information. Upon conclusion of this experiment, the data collected showed that the results positively showed better accuracy in general when the two modalities are combined. The test results confirmed that better accuracy testing is achieved when combining expressive body information and emotion recognition. (Gunes & Piccardi, 2007)

Further studies have shown that using an algorithm for the detection and analysis of emotion using body language alone without any facial expression detection has shown possibly positive results. This article in particular tests emotional and mental states by detecting the pose or posture of a person. Since the study of emotion has shifted from psychology to computing such as Human to Computer Interaction (HCI) it is somewhat less complicated to detect emotions using different methods that might not have been used otherwise. The proposed study used the Pictorial Structure Model (PSM) which provides a framework the pose detection and estimation. At the conclusion of this study, the results showed that without facial expression data it is almost impossible to get accurate results. (Singh et al., Sep 2015)

Studying gesture recognition for emotion detection started with sign language and trying to detect the emotions of the hearing impaired who primarily communicate using sign language. Hand gesture recognition research is classified as Glove based and vision-based studies. Basically, sign language can be static (motionless/posture) or dynamic (lively/gesture).

In the American Sign Language (ASL) glossary, a sign is expressed in four different elements which are:

- Handshape
- Hand movement
- Palm orientation and location in relation to the body

The Sign Language Recognition (SLR) system is already in place and is categorized into two groups which are:

- Vision-based.

- Glove based.

The algorithms that are used in Sign Language Recognition follow a line of investigation involving artificial neural networks, computer visions, and linguistics. (Jayanthi & Sathia Bhama, Dec 2018)

Multimodal mixed emotion detection in recent studies has shown that this method is used to automatically detect emotional duality and various emotional experiences by capturing data using an audio-visual continuous data stream. The data collected is used by this method using an infrared sensor named Kinect. Additionally, the OpenEar software and Face API are toolkits used for the calculation of the different features. The results of this data collection method have shown an overall accuracy rating of mixed emotion recognition of 96.6%. The accuracy from facial recognition alone is 92.4% and head movement is 94.3%. (Patwardhan, 2017)

Emotion recognition is mostly used in medicine, education, marketing, security, and surveillance. The goal of this mixed modal research was to develop an algorithm to detect facial expressions, head, and hand gestures, and body postures that will be used to train a support vector machine (SVM) based classifier to identify multiple emotions. However, the problem discovered during testing lies within the multi-label classification section. (Patwardhan, 2017)

The infrared sensor Kinect manufactured by Microsoft is used to implement a multimodal emotion recognition system. The input from this recognition system consists of audio-visual channels. The audio-visual portion provides 3D data from face-to-face, head, hand gestures, and body movement. The OpenEar toolkit provided data that was captured via audio-visual equipment. The objective of this experiment is in two parts:

- The use of 3D will have features from facial expressions to include.

- Head
- Hand
- Body in combination with vocal features to recognize more than one emotion at the same time.

- To provide a benchmark result for the multi-label classification problem identified during the initial testing. (Patwardhan, 2017)

For feature selection, this study used human facial expressions. Facial expressions are naturally used to communicate by using the eyes, eyebrows, lips, cheeks, and region around the mouth all of which are expressive parts of the human face. Using body features including body modality tracking, the center of the spine, center, left and right hip, knee, and ankles were tracked. All existing studies are from the field of psychology and behavioral sciences which focus only on two emotions which are dual emotions and ambivalent emotions. Future studies can focus on more than two emotion combinations with a larger more diverse group of participants to be included to study different cultures, gender, and language to simultaneously capture expressed mixed emotions. (Patwardhan, 2017)

More recent studies have shown that applying a sentiment analysis algorithm can reveal positive results in emotion recognition. There are many researchers that have contributed to the development of emotion recognition algorithms. These algorithms capture data from gestures, or emotion recognition. This experiment shows that combining gesture detection obtained from the Kinect toolkit and the text description of each body movement along with existing spoken sentences from the participants can possibly reveal the emotional state of the user. (Gentile et al., 2017)

This study proposed a system that recognized emotions from body movements or gestures using the Kinect database. It is assumed that each gesture is associated with a text description. In this experiment, the most adopted mathematical framework used was the Hidden Markov Models (HMMs). The results of this experiment showed that perhaps it is possible to recognize emotions directly from body gestures using the right dataset, toolkits, algorithms, applications, and equipment along with careful preparation. (Gentile et al., 2017)

Research has shown that non-verbal cues such as facial expressions and gestures contain affective information that can be used to detect human emotional states with high accuracy. Emotion recognition detection in this study is captured by applying a framework of hierarchical sequences that consist of three levels. The three levels are:

- Actions
- Gestures: Recognition of gestures are based on three modalities:
    - Head
    - Face
    - Body
- Emotions

This study has claimed to have presented a system in real-time that can automatically detect and infer the mental and emotional state of humans by incorporating video sequences to be labeled continuously. (Baltrušaitis et al., Oct 29, 2010)

RELATED WORK

There are many studies done on stress detection using Facial Expression Recognition, wearable biosensors, and other ways to capture this data. Some analyses have been close to accuracy and many others have been inconclusive. The aim of this work is to find an accurate, real-time, reliable, unobtrusive way to detect stress and offer resolution in a short amount of time. Healthcare studies have shown that symptoms of chronic stress are on the rise. The gap in health care research and stress detection research is accurate real time capture and quick turn-around resolution. This is needed in professionals that work in constant, stressful situations, every day. Specific related work details are explained as follows:

Studies using smartphones with embedded sensors as a way of automatically detecting stress have increased. The use of smartphones seemed to be a sensible way to detect stress in a working environment. This study concentrated on the relationship between high-stress levels and stressful working environments. (Garg et al., 2021) The testing was done using a public dataset, chest, and wrist-worn devices. The dataset used was WESAD for the purpose of stress detection and for capturing data, the chest-worn device was RespiBan Professional, and the wrist-worn device used was Empatica E4. (Garg et al., 2021).

RespiBan, the chest device captured information from the ACC (acceleration), ECG (electrocardiogram), TEMP (body temperature), and EDA (electrodermal activity sensors that were embedded in the device. For classification purposes, five machine learning algorithms were used. The algorithms used were Random Forest, k-Nearest Neighbor, Linear Discriminant Analysis, AdaBoost, and Support Vector. Although the results are not conducive in my study they were as follows:

- Using the dataset WESAD in conjunction with the sensors and the classifiers, the observation was that the classifier Random Forest outperformed the other classifiers. (Garg et al., 2021).

A similar study found used a sensor-embedded headset. The sensors inside the headset were the EEG (Electroencephalogram) and the ECG (Electrocardiogram). These have previously been shown to capture the best results in stress detection and rising stress levels. (Lee et al., 2020) Measuring stress by capturing physiological signals has increased in recent studies. These signals have been captured by using the HRV (Heart Rate Variability), EDA (Electro Dermal Activity), and EMG (electromyogram). Using the headband with these sensors has reported an 89% accuracy rating. Additionally, using a normal-sized EEG has proven to be inefficient due to its size and weight and is inoperable in real-life working situations. (Lee et al., 2020)

Additional work has been done using static and dynamic features of the human face. (Yin et al., 2017) The initial stages of the study were done using static and dynamic features of the face was because to establish and verify identity for security purposes. The logic behind this study was to gather as much information from the face as possible.

Historical studies have shown that the human face holds so much information regarding human behavior and studying its biometric information can be useful in obtaining a better understanding of social communication. (Yin et al., 2017) Using facial feature extraction has been shown to be beneficial when establishing a baseline of study. In this study feature extraction is called PCA (Principal Component Analysis), this type of analysis is the process of defining a set of features on the face or images of the face for characterizing.

Additionally, landmarks of the face have been determined to be a very important detail in Facial Expression Recognition. Prominent places on the face are the corners, or tips and midpoints of the face such as the nose. (Yin et al., 2017) More studies found have shown that studying stress by using biometric means has been successful in capturing results with high accuracy. Facial expressions hold a lot of information on someone's mental status. Gaining a fundamental understanding of facial expressions is instrumental in understanding stress without too much intrusion. (Zhang, et al., 2019) The study proposed a framework to incorporate facial expression recognition to detect stress which proved to have a high accuracy rate in real-time. (Zhang, et al., 2019) The classifier used in this study was the convolution neural network and negative emotional detection module. (Zhang, et al., 2019)

Advancements have been made in stress detection using multimodal sensors. Additionally, artificial intelligence and intelligent systems have greatly influenced facial expression for stress detection studies. In this study, a multimodal called a Deep Denoising Autoencoder which includes visual and sound modalities in the process of stress detection was proposed and tested. (Ghosh et al., 2022) This method proved to be accurate in classifying the images as they were being captured.

This method was also able to determine stress from non-stressed images of human facial expressions with an accuracy of 92%. (Ghosh et al., 2022) In other more recent studies attempts are made to detect human stress triggers and symptoms from facial expressions alone. Because panic and anxiety attacks have increased over the years due to increased usage of technology and IOT in general, assessments and prevention studies have intensified as well. Gathering information on someone's mental state from facial expressions has always been important. But recently, using artificial intelligence to detect and analyze has become more of a hot topic of discussion and research.

The database Facial Action Coding System (FACS) is a standard in psychology of understanding emotion which is normally demonstrated in the slightest muscle movements of the face. Also, influenced by other intelligent systems numerous facial expressions recognition and detection algorithms have been developed. One current study proposes using a classical CNN architecture by the name of Alex-Net to analyze stress. This model proved to be impressive by yielding the results of stress detection from facial expression recognition algorithms with 92% accuracy. (Ghosh et al., Jan 01, 2022)

As more studies are emerging, it is apparent that Facial expression recognition (FER) is a complex topic. FER is currently being used in areas such as healthcare, law enforcement, security, safe driving, and cyber security. Computational Facial expression recognition artificial intelligence copies human expressions of the face. Examples of the several ways Facial expression recognition is being used are for security purposes. Malicious intentions can be captured by surveillance cameras installed with Facial expression recognition applications. The data captured in real-time can detect and analyze the emotions of potential criminals.

Furthermore, even though facial expression recognition technology is increasing in promising stress detection, challenges have emerged during current research. (Sajjad et al., 2023) The challenges that have been found are defining the expression, a sparse number of datasets available, illumination or lighting, the position of the face, occlusion in which certain parts of the face are not visible because of beards, glasses, and masks, then there is human aging. These challenges will be discussed further in the challenges section.

As a result of many working days of productivity being lost due to people using sick time because of stress, anxiety, and panic attacks, more research has been done on stress detection.

Studies have shown that someone's facial expressions are a cue to their physical and mental distress.

A more recent study has revealed promising results of Active Appearance Models (AAM) in recognizing emotions based on facial expressions. (Bannore, et al, 2021) A recent survey on Deep Facial Expression Recognition showed that not only are there positive future aspirations but also many challenges also cause many limitations on experiments, tests, and capturing data. The positive signs of capturing stress signals from Facial Expression Recognition with high accuracy are plentiful. One major positive sign is that Facial Expression Recognition mimics human facial expressions. The coding that coincides with computational FER displays very critical facial cues that also compliments speech. (Sajjad et al., 2023) Within the last few years, it has been observed that methods using facial expression recognition for stress detection have grown rapidly. These methods were performed using such as computer vision, deep learning, and artificial intelligence. Recent studies have shown that FER is being used frequently in healthcare, law enforcement, security, and to aid in stress detection and mental health status, as well as depression. (Sajjad et al., 2023)

Using FER in security has been shown to play an important role in detecting malicious intentions on the faces of suspected criminals by analyzing their facial expressions through video surveillance cameras. Additionally, in educational settings, teachers or professors can adjust their teaching techniques based on the facial expressions of their students when delivering certain material. All the methods of how FER are captured there also must be a preprocessing process, that many studies do not discuss in detail. Data can be collected through various ways such as sensors, surveillance cameras, webcams, cell phones and other devices with video capturing or sensor

capabilities. (Sajjad et al., 2023) A portion of the preprocessing process is the ROI or Region of Interest detection. This procedure is used to identify and locate faces within captured images.

This is a common technique used in law enforcement, entertainment, and personal security. (Sajjad et al., 2023) Under normal circumstances, facial expression is the most critical and powerful way to show emotions. It is the most universal and straightforward in showing mental state, stress, and all other emotional states. But people handle emotions very differently which is also shown on the face. A recent study determined that a system was in place to identify mental illness which can perhaps detect emotions and possibly stress detection. The system is an algorithm that uses a weighted Fuzzy Network to show depression in patients. (Rajawat et al., 2023)

The Facial Action Coding System (FACS) was created by Ekman and Friesen in 1983 for the sole purpose of measuring each expression that could possibly be made by the human face by giving them action unit numbers (AUs). Research has shown that very specific combinations of AUs display each of the universal facial patterns of the emotions anger, disgust, fear, sadness, surprise, and happiness. FACS is one of the most widely used coding systems in analyzing facial expressions. There are three ways to score facial actions units which is:

1. Manually
2. Using FER software
3. Using coding software for observation only (Friesen & Ekman, 1983)

CHALLENGES OR GAPS

Many studies have shown that common challenges in using Facial expression recognition keep occurring when trying to detect stress with FER alone. Even though there are common facial landmarks on the human face, there are also different variations of the face.

Such as age, race, gender, obstructions, and culture, all must be factored in why facial expressions as a way of detecting stress. People age differently, and the difference ranges greatly from age to gender, to culture, and exposure to disease or drug abuse or living healthy. The human faces change drastically between males and females and ethnicity. All these differences must be factored in when trying to determine the exact expression and if the person is stressed or not. Using a database with an abundance of different facial expressions can be beneficial. There are also data biases that contribute to the challenges because of the many ways data can be collected and under different conditions. (Li & Deng, 2022) Additionally, previous studies have used a set of standard algorithmic pipelines for Facial Expression Recognition which all focus on traditional methods. Deep learning methods are hardly used at all. (Li & Deng, 2022)

Noticeable limitations have also been discovered when trying to use certain classifiers to analyze the results from Facial Expression Recognition software. Using the Convolutional Neural Network and the AlexNet network classifiers consumed extensive memory storage when analyzing a large dataset which posed a problem. Additionally, several external factors of social, emotional, and mental history created more difficulty in pinpointing the exact emotion or stress trigger captured from facial expression recognition. (Ghosh et al., Jan 01, 2022) Other challenges discovered are the many techniques that have been neglected such as using edge vision-inspired deep learning and Artificial Intelligence based FER technologies. (Sajjad et al., 2023)

Other challenges using FER are defined specifically in data sets, illumination, face pose, occlusion, aging, and low resolution. Defining the exact expression or emotion on a human face can be challenging for human-to-human, but when artificial intelligence is combined, with deep learning, detection can become even more difficult. (Sajjad et al., 2023).

The challenge with datasets is the limited availability and scarcity of large datasets with all necessarily captured expressions. Illumination is a problem because the variation in lighting at different angles and locations can be numerous and complicated at best. The position of the face or the pose is an additional challenge because it changes with the head movement, angle, lighting, and the location of the camera. Occlusion refers to portions of the face being hidden with hats, glasses, facial hair, and possibly face masks. These obstructions normally cause the recognition process to fail. Aging, of course, is the age of the person. Human facial features usually change as the person gets older. To solve this problem in facial expression recognition, a huge amount of data training must be done beforehand. Finally, low resolution in capturing images or in videos because of the difficulty seeing the image or the face. (Sajjad et al., 2023)

Recent studies and experimentations show that older or conventional facial emotional recognition models are less accurate. Another issue that conventional facial emotional recognition models face is misinterpreting an emotion such as labeling disgust as happiness or anger as surprise. In present-day real-time detection, this would produce fewer desirable results. (Durga & Rajesh, 2022) All studies have shown that facial emotions and correct characterization are very important for application features and new technologies. Conventional Facial emotion recognition applications are incapable of capturing the correct emotion especially when occlusion has occurred. Occlusion as described earlier is the obstruction of the face with glasses, masks, mustaches, beards, or any other face coverings. (Durga & Rajesh, 2022)

Recent studies have shown that because of the surge of wireless mobile and electronic devices, there is a large amount of video data online or in the cloud. Because of the massive amounts of video data, facial expression recognition can be applied in various applications. Facial expression recognition can be used in classroom technology, security surveillance, employment, and identity verification. As technology has advanced the reasons for using facial expression recognition have evolved as well. But the traditional methods of facial expression recognition have not been able to keep up with the advancements and the need for real-time facial expression detection. (Guo et al., 2022) Studies have shown that traditional FER methods only focus on the texture information received or only on the key points of extraction for recognizing and expression within an image. This study it shows experimentation tried to alleviate the problems of traditional FER methods by proposing and creating a Multi-region Attention Transformation Framework (MATF) to blend the texture information captured with a multi-dimensional manner of extraction. (Guo et al., 2022) The results show that fusing the multi-region framework with capturing the texture of an image proved to yield high accuracy and recognition of the actual expression. (Guo et al., 2022)

In other studies, using Automated Facial Expression Analysis (AFEA) which is the process of combining facial expression recognition and emotion identification, results are not as accurate as previously thought. The process is not simple because of the various characteristics of each human face. The differences vary by gender, ethnicity, age, and occlusion which are previously explained as obstructions of the face such as hair, hats, masks, and glasses. (Piwowarski, et al., 2022) Machine learning, deep learning, and computer vision along new technologies are in the process of trying to solve the problem of identifying the various human emotions accurately and in real time. (Gupta, et al., 2020)

A completely different study offered a proposed method of a more efficient way to identify the many different human emotions. Computer applications may seemingly offer a faster way of communication, but by doing so, it alters the answers in various encounters usually depending on the user's emotional state. (Sarvakar et al., 2021) The challenge with the computer applications method is that for accurate results, a large amount of test data and keywords are needed as well as a graphics processing unit (GPU) is also required. With a high-performing computer, more accurate results may be achieved.

Deep learning techniques are powerful enough to learn numerous facial features which are currently being used in facial expression recognition applications. But the various facial characteristics still create problems when trying to apply deep learning techniques using current datasets. The available datasets are not trained efficiently enough to achieve human-like accuracy. (Gupta, et al., 2020) It is very difficult for machines to understand the complexity of detecting expressions effortlessly like humans. There are many steps to training a machine to detect just basic emotions. There are two methods in facial expression detection automation, which are (1) Static expression detection and (2) dynamic expression detection. Static is detecting an expression from one image of a human face at a time. Whereas dynamic expression detection is using multiple frames of human expressions at one time. Then there is detecting facial emotion and analyzing which consists of three steps. The three steps are (1) acquisition of the face, (2) extraction and correct representation of the data (3) recognition of each facial emotion. (Gupta, et al., 2020)

More recent studies have proposed using a mobile network named MobileNetV1. This model optimizes the loss function and the architecture combined with previous models. (Nan, et al., 2022) Another more recent study shows that by introducing a model that detects the face and identifies the emotions automatically, using a three-step process.

The steps are (1) face detection, (2) feature extraction and (3) classification of expressions. (Albraikan et al., 2022) Traditional Facial Expression Recognition applications normally contain two major stages which are emotion recognition and feature extraction. But the primary function of facial expression recognition is to match the corresponding emotional state to several facial expressions. This study proposed the model of Intelligent Facial Expression Recognition-Deep Transfer Learning (IFER-DTFL) to automatically detect emotions automatically.

The classification equivalents to the three-step process are the Mask RCNN, ResNet50, and Adam optimizer. Benchmark datasets were used with each simulation to demonstrate better performance using the IFER-DTFL model. The results after each simulation showed that the IFER-DTFL model had more accurate results. Future proposals should show how the performance of Intelligent Facial Expression Recognition – Deep Transfer Learning has improved by using metaheuristic optimization techniques. A metaheuristic method helps in solving the optimization problem. Problems in optimization can be found in many daily life aspects. (Albraikan et al., 2022)

CONCLUSION

In conclusion stress and anxiety are two forms of physical and psychological tensions. These two uncomfortable and dangerous forms of tension in the human body can affect someone's daily work performance. (Widanti, et al., 2015) In the cybersecurity profession, the safety of critical information lies in the hands of these professionals.

These studies are aimed to detect stress levels at various levels and learn what exactly triggers stress during various situations. The final goal is to offer comfort and resolutions to keep stress at a minimum during the workday to keep the employee's health and well-being safe as well as the safety of the digital information he or she is protecting from cyber-attacks.

As previously mentioned, the various methods used to detect stress are using different biosensors that capture data from various parts of the body. Additionally, these stressful situations can be captured and monitored on video cameras set up during simulations of stressful situations. Also described in detail previously are the different biosensors that are used to capture blood pressure, skin resistance, heart rate, brain waves, and muscle responses. All these electric responses also show on the face with different facial expressions.

Along with video recording will be facial expression recognition software used to analyze each expression. Again, each of these features will be used to aid employers to detect stress better in their employees during the workday, especially in high-level cybersecurity professions. There are many methods and technologies used to detect stress and emotional stress in individuals. Studies have shown that the most reliable or high accuracy ratings come from using multiple modes and various sensors to capture data. (Greene, et al., 2016) Studies have also shown that emotions play a critical role in motivation, perception, and decision-making.

So, if emotions are running "high" because of a prolonged stressful situation, the employee may be prone to making a serious mistake or not caring at all about the severity of the situation at hand. (Hosseini & Khalilzadeh, 2010) Affective Computing is a growing field of technology that can effectively detect stress and various emotional states using multi-model sensors to capture data. (Greene, et al., 2016)

The intentions of this literature review are to have done an exhaustive search on all studies done on stress, anxiety, and emotional health and how each left untreated can negatively affect the cybersecurity professionals of our society.

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